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The Impact of Positive Technology Readiness Traits and Trait Curiosity on Generative AI Adoption for Learning Purpose: An Empirical Study in Vietnamese Context

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ABSTRACT

Generative Artificial Intelligence (GenAI) is reshaping multiple industries across the globe, and education is no exception. This study aims to explore the influence of positive technology readiness traits and trait curiosity on Vietnamese university students' intention to use Generative AI for learning purposes, using the Uses and Gratifications Theory. The research model was empirically tested using 339 responses conducted from Vietnamese university students. The findings of research confirmed that perceived intelligence, achievement, social presence, and status positively influence students' intention to use GenAI for learning, while perceived enjoyment has no significant effect. The research results also revealed that trait curiosity also played an important role in the adoption of GenAI for learning purpose.

Keywords: Generative AI Adoption; Uses and Gratifications Theory; Technology Readiness Traits; Trait Curiosity; Perceived Intelligence; Innovativeness.

1. Introduction

Artificial Intelligence (AI) with the most transformative developments is Generative AI (GenAI) such as ChatGPT and Sora is reshaping multiple industries across the globe, and education is no exception (Cong-Cong et al., 2024). These technologies are capable of generating coherent, context-sensitive text, images, and code, with ChatGPT standing out for its ability to engage in multimodal conversation, perform complex analysis, and offer highly personalized support. This

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makes it particularly well-suited for educational applications, enabling instant feedback, tailored learning pathways, and a more engaging, autonomous learning experience (Mogavi et al., 2024; Obenza et al., 2024). According to Bai et al. (2023), GenAI tools have smart functionalities rely on advanced natural language processing and machine learning techniques, allowing them to respond meaningfully to user inputs while adapting to individual learning needs. These intelligent capabilities have made GenAI tools powerful educational companions, transforming how students access, process, and apply knowledge. Globally, AI-driven chatbots are increasingly deployed in educational environments, offering support in tutoring, writing, problem-solving, and more (Clarizia et al., 2018). Over the past few years, the integration of AI into education has accelerated across Southeast Asia. Countries like China, Malaysia, and Singapore have incorporated AI education into their national curricula, investing in teacher training, AI centers, and real-world applications ranging from robotics to code generation. In Vietnam, the Ministry of Education and Training (MOET), in collaboration with UNICEF, has launched strategic initiatives to equip both students and educators with AI competencies. At the National Forum on Artificial Intelligence in Education, leaders emphasized the importance of developing responsible, proactive, and ethical AI usage in schools. Despite these developments, the practical adoption of GenAI tools by Vietnamese students is still at an early stage. While the technology is readily accessible, empirical studies investigating the psychological and behavioral drivers behind students' use of GenAI in learning contexts are scarce. Specifically, very little is known about how individual traits such as optimism, innovativeness, or trait curiosity interact with students' motivations to adopt GenAI tools.

Traditional models such as the Technology Acceptance Model (TAM) and the Information Systems Success Model (ISSM) provide a solid foundation for understanding technology adoption (Wang et al., 2023). However, these frameworks may fall short in accounting for the unique, personalized, and emotionally gratifying experiences GenAI tools provide. Given the distinctive affordances of GenAI, there is a clear need for theoretical approaches that can better reflect these subjective, motivational, and psychological dimensions. The Uses and Gratifications (U&G) theory (Katz et al., 1973) offers a suitable lens to explore such behaviors. Originally developed to examine media usage, U&G theory has since been applied to digital platforms and interactive technologies (Khan, 2017). Nevertheless, research applying U&G to AI-powered educational tools remains limited. Existing studies often overlook core gratification dimensions such as perceived intelligence, status, or social presence, factors that may significantly influence students' motivation to engage with GenAI.

To address these gaps, this study integrates the Technology Readiness Index (TRI), trait curiosity, and an extended U&G framework to investigate what drives university students in Vietnam to adopt GenAI for learning. Through this lens, the research aims to uncover how psychological readiness, personality traits, and gratification needs influence behavioral intention. The findings are expected to offer both theoretical insights and practical implications for educational institutions and developers working to foster responsible and effective AI integration in academia. The paper is structured as follows. In the next sections we will discuss the conceptual model development with proposed hypothesis, methodology, results, and conclusion.

2. Literature Review

2.1. Artificial Intelligence and Generative AI

Artificial Intelligence (AI) is a branch of computer science dedicated to creating systems capable of performing tasks that usually require human intelligence (Lee & Lee, 2021). Initially, Artificial Intelligence (AI) is generally described as the capability of machines to replicate human cognitive abilities, including learning, reasoning, and perception (Russell & Norvig, 2016). Today, AI encompasses various subfields such as natural language processing (NLP), computer vision, and reinforcement learning, contributing to its widespread application across industries (LeCun et al., 2015). AI's ability to learn from data, improve performance, and adapt to new information highlights its transformative impact on industries such as healthcare, finance, and education (Esteva et al., 2017; Loeckx, 2016; Tahiru, 2021; Zhai, Nyaaba, & Ma, 2024). Research suggests that AI can serve as an effective learning tool, reducing the burden on both teachers and students while offering enhanced learning experiences (Zhai et al., 2024).

Generative Artificial Intelligence (GenAI) is a subfield of artificial intelligence that employs advanced computational techniques to generate new, contextually meaningful content, including text, images, audio, video, and three-dimensional models, based on training data (Dwivedi et al., 2023). The development of transformer models in 2017 further accelerated the progress of generative AI. Transformers, which enabled researchers to train larger models on vast datasets, made it possible to generate more accurate and realistic responses to text prompts (Vaswani et al., 2017). These innovations paved the way for the creation of Generative Pre-trained Transformers (GPT), introduced in 2018, which further revolutionized the generative AI landscape (Mostafazadeh et al., 2016; Radford et al., 2018). Today, generative AI has become a transformative technology that is reshaping industries by enabling the creation of diverse types of data. Examples of generative AI applications include DALL-E 2, GPT-4, ChatGPT, and Copilot, all of which are employed for tasks such as content creation, communication, and problem-solving. The global impact of generative AI is anticipated to be significant, with predictions suggesting that it could increase global GDP by 7% and potentially replace 300 million jobs in knowledge-based sectors (Sachs, 2023).

2.2. Uses and Gratification Theory

The Uses and Gratifications (U&G) theory suggests that individuals are active, goal-oriented users who engage with media and technologies to meet specific social and psychological needs (Katz, 1959; Ruggiero, 2000). Unlike traditional models like the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which primarily concentrate on functional aspects such as perceived usefulness and ease of use, U&G highlights the user's proactive role in selecting technologies that offer personal gratification (Katz et al., 1973; Venkatesh et al., 2003).

A notable advantage of the U&G theory is its ability to encompass not only functional aspects but also emotional and psychological factors in technology use, which are often overlooked in more traditional models (Chi et al., 2024). These models, such as TAM and UTAUT, focus on the instrumental characteristics of technology use but fail to capture the complex social and emotional factors that influence user behavior after adoption (Venkatesh et al., 2003). In contrast, U&G offers a more comprehensive understanding by accounting for the satisfaction and emotional gratification derived from using GenAI technologies, especially in the post-adoption phase, where users' intrinsic

motivations and needs play a significant role in their continued engagement with the technology (Bagozzi, 2007; Gao, 2023).

In this context, U&G theory offers a more nuanced explanation of why students may adopt GenAI for educational purposes. According to Rauschnabel and Ro (2016), the motivations for using technology can be categorized into four key dimensions: utilitarian, hedonic, symbolic, and social benefits. The researchers also suggested that utilitarian benefits may include using GenAI to gather information for academic tasks, such as learning new concepts or completing assignments efficiently. Hedonic benefits, on the other hand, could involve the enjoyment and mental stimulation derived from interacting with a sophisticated AI tool, which provides both entertainment and cognitive engagement (Babin et al., 1994; Schuitema et al., 2013).

Hedonic benefits	Utilitarian benefits	Social benefits	Symbolic benefits

Fig. 1. Uses and Gratifications theory

Source: Rauschnabel et al. (2018)

Additionally, symbolic benefits could be relevant for students who use GenAI to enhance their image as technologically savvy or knowledgeable, particularly in academic environments where technological fluency is valued (Grellhesl & Punyanunt-Carter, 2012).

Furthermore, the social benefits of using GenAI in the educational context should not be overlooked. As noted by Osei-Frimpong and McLean (2018), the social presence and interaction experienced by users in technology-driven environments can serve as a powerful motivator. For students, using GenAI could fulfill social needs, such as seeking affirmation or a sense of connection with a virtual assistant that provides personalized and responsive engagement (Biocca et al., 2003). Therefore, by applying the U&G theory, it is possible to gain deeper insights into the multifaceted reasons why students may choose to use GenAI as an educational tool, considering both their functional and emotional needs (Grellhesl & Punyanunt-Carter, 2012).

2.3. Positive Technology Readiness Traits and Trait Curiosity

Technology Readiness refers to "people's propensity to embrace and use new technologies for accomplishing goals in home life and at work" (Parasuraman, 2000). Technology Readiness is a concept composed of both enabling and inhibiting factors, including Innovativeness and Optimism as facilitators, and Discomfort and Insecurity as barriers. These factors play a critical role in shaping an individual's willingness to adopt new technologies. However, the influence of Technology Readiness and its components (optimism, innovativeness, insecurity, discomfort) may vary depending on the context. For example, in the context of smart tourism technologies, research found that Innovativeness and Optimism had a positive effect on travelers' satisfaction, while Insecurity did not significantly impact it (Pradhan et al., 2018). Further studies by Hailey Shin et al. (2021), and Iyer et al. (2021) also suggest that the inhibiting factors (such as insecurity and discomfort) either have a minor role or are non-significant. Research on mobile electronic medical records Kuo et al. (2013) also highlights that Innovativeness is a key determinant in the Perceived Ease of Use and Perceived Usefulness of technology.

Trait curiosity, defined as an individual's stable tendency to seek new knowledge and explore novel experiences, has been widely recognized as a critical factor in technology adoption (Litman, 2010). Empirical studies have shown that curious individuals are more likely to engage with unfamiliar technologies due to their innate inclination toward information-seeking behaviors (Langevin, 1971). Previous research has identified that curiosity positively influences purchase intentions (McGillivray et al., 2015) and the adoption of emerging digital tools, including mobile learning technologies (Menk dos Santos, 2015), smartwatches (Mnih & Salakhutdinov, 2007), and 5G innovations (Shoaib et al., 2024). Given that curiosity enhances cognitive engagement and motivates users to explore new technologies, it is expected to play a significant role in shaping students' behavioral intention to use GenAI for learning purposes.

3. Conceptual model development

3.1. Perceived Intelligence

Perceived intelligence is a critical factor in determining user acceptance and interaction with intelligent systems, as it directly influences trust and perceived usefulness (Moussawi et al., 2023). Prior research has demonstrated that users are more inclined to engage with and trust a system when they view it as highly intelligent (Jiang et al., 2017). Specifically, perceived intelligence-defined as the extent to which users believe a system displays cognitive functions such as learning, reasoning, and adaptability - plays a vital role in building user trust and shaping behavioral intentions (Vorisek et al., 2023).

The connection between perceived intelligence and user adoption of technology has been extensively explored in the context of intelligent agent systems. Research indicates that systems seen as highly intelligent foster greater trust, which then boosts their perceived usefulness and the likelihood of continued usage (Moussawi et al., 2023). Moreover, studies on human-computer interaction suggest that when a system shows the ability to solve problems and respond quickly, users are more likely to view it as competent, which increases their intention to keep using the technology (Lee & Lee, 2021). This effect has been confirmed in various settings, such as personal intelligent assistants and Internet of Things (IoT) systems, where a higher perceived intelligence significantly impacts users' behavioral intentions (Jiang et al., 2017).

In the case of GenAI, students' perceived intelligence of the system has been shown to impact their willingness to use it for academic purposes (Vorisek et al., 2023). When users perceive GenAI as highly intelligent, capable of providing meaningful responses, understanding complex queries, and adapting to their needs, they are more likely to trust and rely on the system, which ultimately strengthens their intention to use it for learning (Moussawi et al., 2023). Based on this established relationship, it is hypothesized that students who perceive GenAI as highly intelligent will demonstrate a stronger intention to adopt and continuously use the platform for educational purposes (Jiang et al., 2017). Therefore, this study proposes the following hypotheses:

H1. Perceived intelligence is positively associated with intention to use GenAI for learning purposes.

3.2. Achievement

Achievement, particularly in the context of digital learning, is closely linked to utilitarian gratification, which refers to the practical and goal-oriented benefits derived from technology use (Pujadas-Hostench et al., 2019). Empirical studies indicate that when users perceive a tool as

instrumental in helping them reach academic or personal goals, they are more inclined to continue using it (Ryan & Deci, 2000). In e-learning environments, achievement is often reinforced through mechanisms such as earning points, leveling up, and completing milestones, which significantly contribute to sustained technology adoption (Lampropoulos et al., 2022). Choi et al. (2021) further demonstrated that achievement-driven motivations positively influence users' behavioral intention to continue using educational smartphone applications. Given that GenAI functions as an AI-powered learning assistant, students who derive a sense of accomplishment from using it whether through improving academic performance, enhancing writing quality, or mastering subject areas are more likely to integrate it into their study routines.

The need for achievement (nAch) has been recognized as a fundamental driver of technology adoption and engagement in academic contexts (McClelland, 1988; Schmidt & Frieze, 1997). Individuals with a high nAch tend to seek tools that enhance their learning capabilities, improve problem-solving skills, and enable them to attain academic milestones (Zenzen, 2002). Prior research has found that users with strong achievement motivation engage more actively with learning technologies to outperform their peers, gain academic recognition, and develop subject mastery (McClelland, 1988). Additionally, Chiang et al. (2014) emphasized that the ability to achieve more than others within a digital learning environment strengthens users' behavioral intention to continue engaging with the system.

Given that achievement is a core component of utilitarian gratification, students who derive a sense of academic accomplishment from using GenAI may perceive it as an effective tool for enhancing their learning outcomes. Thus, this study puts forth the following hypothesis:

H2. Achievement positively influences intention to use GenAI for learning purposes.

3.3. Perceived Enjoyment

Perceived enjoyment, a central element of hedonic gratification, has been widely recognized as an important factor in technology acceptance and usage behavior (Shiau & Luo, 2013; Venkatesh et al., 2003). Defined as the extent to which users find an activity intrinsically enjoyable, independent of its practical benefits, perceived enjoyment has been shown to significantly influence users' engagement with technology and their long-term adoption behaviors (Davis et al., 1992; Ryan & Deci, 2000). Empirical research consistently demonstrates that when users enjoy using technology, their motivation to continue engaging with it strengthens, which in turn increases their behavioral intention to use the technology (Gallego et al., 2016).

In the context of adopting GenAI for educational purposes, perceived enjoyment plays a crucial role in shaping students' willingness to incorporate this technology into their academic routines. GenAI facilitates interactive and engaging conversations, promoting emotional involvement and playfulness, thereby enhancing the overall user experience (Chaves & Gerosa, 2021). The AI-driven conversational nature of GenAI allows users to experience a sense of social presence and human-like interaction, contributing to greater satisfaction and continued use of the technology (Wu & Yu, 2024). Previous studies on internet-based entertainment platforms (Agag et al., 2019) and digital learning tools (Van der Heijden, 2003) have identified perceived enjoyment as a strong predictor of users' behavioral intention to adopt technology. In line with these findings,

Hailey Shin et al. (2021) emphasized that GenAI users often experience emotional interactions that contribute to their enjoyment, further promoting their continued engagement with the chatbot.

Furthermore, Ha et al. (2024) confirmed that users' perceived enjoyment of GenAI positively influences their intention to use the system again. From this empirical finding, it can be inferred that when students experience pleasure while using GenAI, they are more inclined to develop a stronger intention to continue using it for academic tasks. Therefore, we propose the following hypothesis:

H3. Perceived enjoyment positively influences intention to use towards GenAI

3.4. Social Presence

Since the advent of the first commercial computer, there has been an increasing interest in engaging in conversations with machines (Hoy, 2018). Studies in robotics have revealed that the social presence of machines is becoming more apparent (Chattaraman et al., 2019). Automated social presence is defined as the extent to which machines can make people feel like they are interacting with another social being (Heerink et al., 2010). According to Short et al. (1976), social presence is the degree to which a person is perceived as a significant part of the interaction.

The studies conducted by Nass and colleagues (Callaway & Sima'an, 2006; Fogg & Nass, 1997; Nass & Moon, 2000; Reeves & Nass, 1996) provide a comprehensive understanding of how humans perceive computers as social entities. These studies indicate that when computers use natural language, engage in real-time interactions, and even take on traditional human roles (such as customer service representatives in banks), even experienced users tend to treat these machines as social entities. Nass and Moon (2000) argues that, as inherently social beings, humans apply social roles in their interactions with technology, such as using politeness, waiting for responses, and making gestures, just as they would when interacting with another person. Lombard and Ditton (1997) found that machines can trigger social responses by imitating human characteristics such as voice, appearance, and behavior. Wang et al. (2021) further highlights that features resembling human traits evoke social responses, with language-based interactions between people and AI devices being a critical factor in creating social presence. As individuals grow more comfortable interacting with AI personas, similar to human communication, they develop a connection with virtual assistants (Cerekovic et al., 2016). Cialdini Robert (2021) suggests that people are more drawn to those who exhibit pleasant behavior, which enhances their social attractiveness. Jung et al. (2017) observe that robots can not only assist users but also offer companionship. Therefore, this study proposes the following hypothesis:

H4. Social presence positively influences intention to use towards GenAI.

3.5. Status

Status, a key element of social gratification, has been recognized as a major driver of technology adoption and continued usage (Ji & Wayne Fu, 2013). Based on the Diffusion of Innovations Theory (Rogers et al., 2014), the desire for social status plays a critical role in influencing individuals' interactions with digital platforms. Technology adoption is not solely driven by functional benefits but also by the aspiration to enhance one's social standing. In this context, the pursuit of status has been identified as a key motivator that fosters the long-term use of digital tools (Gallego et al., 2016).

Empirical studies have consistently shown that status-related motivations significantly impact users' intentions to engage with technology. Chiang et al. (2014) found that individuals who view a digital tool as a means of enhancing their social prestige are more likely to adopt and continue using it. Similarly, Plume and Slade (2018) noted that online platforms help users project their self-status and facilitate self-presentation, further strengthening their engagement with technology.

Previous research suggests that individuals often seek to establish their personal identity and gain recognition through digital interactions (Bendersky & Shah, 2013; Leung, 2013). Given that GenAI allows students to present themselves as knowledgeable and technologically adept, status-driven motivations could significantly enhance their intention to use this tool for academic purposes. Therefore, this study aims to explore the role of status in the context of GenAI, with the following hypothesis:

H5. Status positively influences intention to use GenAI for learning purposes.

3.6. Trait Curiosity

In the context of AI-driven learning, students with high trait curiosity are likely to perceive GenAI as a valuable tool for knowledge exploration and intellectual discovery. Curiosity-driven individuals actively seek to bridge knowledge gaps and engage in deeper information processing, which enhances learning efficiency and memory retention (Kang et al., 2009; McGillivray et al., 2015). Furthermore, research indicates that curiosity significantly influences users' willingness to explore AI-based educational tools due to their interactive and exploratory nature (Berlyne, 1950; Maslow, 1943).

Moreover, the I/D model of curiosity proposed by Litman (Litman, 2008) suggests that curiosity consists of two main dimensions: interest-driven curiosity and deprivation-driven curiosity. While interest-driven curiosity increases the pleasure of discovering new information, deprivation-driven curiosity motivates individuals to bridge knowledge gaps even when the process may be challenging. In the case of GenAI, students with high trait curiosity may perceive this AI tool as both an engaging resource for intellectual enrichment and an efficient mechanism for problem-solving and academic support. This dual function reinforces their behavioral intention to use GenAI as a learning assistant, thereby enhancing their long-term engagement with the technology.

Thus, this study puts forth the following hypothesis:

H6. Trait Curiosity will positively impact intention to use.

3.7. Positive Technology Readiness Traits

3.7.1. Optimism

Optimism, as outlined by Parasuraman (2000), holds a crucial position in shaping individuals' perceptions of new technologies, particularly in the case of emerging technologies like Generative AI (GenAI), with a notable example being GenAI. People with an optimistic mindset tend to view such technologies as accessible and user-friendly, believing that they are easy to learn, use, and adapt to. Additionally, they perceive these technologies as tools that can enhance productivity. This optimistic perspective encourages individuals to approach GenAI with an open mind, fostering confidence in their ability to fully utilize its potential. As a result, they are more likely to explore and

leverage the positive value that GenAI can bring to various aspects of their lives, particularly in areas related to efficiency and innovation (Rana & Rai, 2025).

Optimism plays a significant role in shaping how individuals perceive technology and their capacity to use it effectively. Research suggests that individuals with higher levels of optimism tend to view technology more positively and are more likely to recognize its potential benefits (Ghazali et al., 2024). According to Kelberer, Kraines and Wells (2018), optimistic individuals generally focus on the positive aspects of their environment, including the perceived advantages of new technologies. This positive bias towards technology suggests that optimists are more inclined to perceive technology as an effective tool, which may contribute to their ability to harness its full potential. In addition, optimism is closely associated with cognitive processing abilities, which are integral to the concept of intelligence. Based on their study, the researchers also confirmed that optimists are often better at processing positive information and have a greater capacity to identify and utilize the functional benefits of technology. This heightened cognitive focus may enhance their perceived intelligence, especially when interacting with innovative tools like GenAI for learning. Therefore, it can be hypothesized that:

H7. Optimism will positively impact perceived intelligence

Research indicates that optimistic individuals tend to perform better and achieve more than their pessimistic counterparts, often exceeding their potential (Ramli et al., 2023). Specifically, students with an optimistic attitude have been shown to attain higher academic grades compared to those with a pessimistic outlook. Findings from the study noted that optimism is a key component of positive psychology that influences one's overall achievements. According to Prayitno et al. (2017), optimism is closely linked to positive outcomes, such as overcoming obstacles and achieving success. These studies suggest that an optimistic outlook is a key factor in driving achievement, making it an essential trait for students when utilizing new technologies like GenAI for learning. The connection between optimism and achievement is also supported by various studies on task performance, which found a positive relationship between optimism and the ability to perform tasks successfully (Kluemper et al., 2009; Medlin & Green, 2009). This connection highlights the significant impact that optimism can have on students' willingness to use GenAI for educational purposes, as students with an optimistic outlook are more inclined to view it as an effective tool for reaching their academic objectives. Therefore, the researchers proposed the following hypothesis:

H8. Optimism will positively impact achievement

Highly optimistic individuals tend to interpret daily information in a positive light and focus on factors that contribute to favorable outcomes (Scheier & Carver, 1992). For instance, optimistic users are confident in their ability to cope with any challenges associated with technology, which further enhances their overall enjoyment. This positive mindset enables them to effectively cope with stress and challenges, directing their attention towards achieving desired results. As such, optimistic individuals are more likely to engage in activities that lead to positive emotional experiences, including the use of technology, due to their belief in their ability to succeed (Bandura, 1986). Research has shown that optimism enhances hedonic motivation, specifically the pleasure and enjoyment derived from an activity (Ramos Galarza, 2021). Optimistic individuals are more likely to experience positive emotions while using technology, such as GenAI for learning, and are more inclined to perceive it as an enjoyable activity. Given these insights, it can be hypothesized that

H9. Optimism will positively impact perceived enjoyment

Research has shown that optimistic individuals tend to approach social situations with a more positive and open mindset, which fosters more engaging and fulfilling interactions (Räikkönen et al., 1999). These positive interactions contribute to a heightened sense of connection and involvement, key elements of social presence. Furthermore, optimistic individuals are more likely to experience positive emotions during social interactions, which can lead to a stronger sense of social presence (Scheier & Carver, 1992). Increasing research has also shown that social interactions are generally more positive for optimists, contributing to their overall social presence (Dougall et al., 2001; Park & Folkman, 1997). Optimistic individuals, therefore, are likely to experience higher levels of social presence while engaging with GenAI, further reinforcing their intention to use the technology for learning. Given these insights, it can be hypothesized that

H10. Optimism will positively impact social presence

Research suggests that individuals with a higher level of optimism tend to have a more positive outlook on new technologies and are more likely to engage with them, viewing such engagement as a means to enhance their social standing (Scheier & Carver, 1992). Optimists are often proactive in adopting new technologies, and their positive attitude towards these innovations allows them to be seen as more capable and forward-thinking, thereby increasing their perceived status in social contexts (Venkatesh et al., 2003). Being optimistic can create a sense of personal achievement and success, which is often linked to a higher social status. This is particularly evident in technology adoption, where individuals who are early adopters are frequently regarded with admiration for their ability to stay ahead of technological trends. Optimistic individuals, through their early engagement with technologies such as GenAI, may be seen as knowledgeable and innovative, attributes that contribute to their elevated status among peers (Rogers, 2003). Moreover, optimism influences the way individuals are perceived in social groups. Optimistic individuals tend to be more confident and influential in their social circles, which can further enhance their status. This connection between optimism and status is particularly relevant in academic and technological contexts, where individuals are often judged by their ability to adapt to and excel with new tools. The adoption of GenAI for learning could, therefore, be viewed as a way to increase one's perceived status among peers, as students who engage with such technologies are often seen as more intellectually advanced and capable (Bennett & Maton, 2010). Based on these insights, it can be hypothesized that

H11. Optimism will positively impact status

Individuals with an inherent curiosity about their surroundings and a willingness to explore new experiences are more likely to have a positive outlook on the role technology can play in their professional lives. This implies that their level of optimism regarding technological progress is typically high, as they tend to recognize the potential benefits that technology can bring. A study by Gilly et al. (2012) showed a strong positive relationship between users' acceptance of network technologies, their curiosity, and their optimism toward technology. In the field of entrepreneurship, additional research has also confirmed the positive connection between curiosity and optimism (Jeraj, 2014; Papenhausen, 2010). Building on these findings, the researchers have put forward the following hypothesis:

H12. Trait curiosity will positively impact optimism

3.7.2. Innovativeness

Innovativeness, as described by Parasuraman (2000), refers to the propensity of an individual to seek out and embrace new technologies. In the context of consumers' willingness to adopt virtual reality services, studies have indicated a positive link between performance expectancy and personal innovation, which is closely tied to innovativeness (Jingen Liang & Elliot, 2021). Similarly, research on consumers of wearable medical devices highlighted that innovativeness has a significant effect on performance expectancy (Jin, 2020). In the field of electronic payments, Mustafa et al. (2022) found a strong, positive connection between innovativeness and perceived utility. Individuals with higher levels of innovativeness are more inclined to explore the potential advantages of new technologies, often taking on the role of early adopters or innovators in using these technologies.

Innovativeness is often associated with an individual's willingness to embrace new technologies and creative solutions (Stewart et al., 2013). When individuals possess higher levels of innovativeness, they are more likely to perceive technology as more intelligent, expecting it to meet their needs in novel and efficient ways (Venkatesh et al., 2012). Previous research has shown that individuals with higher levels of innovativeness tend to seek out technologies that offer cognitive benefits, viewing these technologies as intelligent tools capable of enhancing their learning experiences (Balkaya & Akkucuk, 2021). In the context of educational technology, students with high levels of innovativeness are more inclined to see tools like GenAI as intelligent resources that can effectively support their academic endeavors. Studies have indicated that teachers' innovativeness influences their beliefs about using information technology in the classroom, which in turn impacts their intention to adopt such technologies (Bervell et al., 2022). Hence, it can be hypothesized that:

H13. Innovativeness will positively impact perceived intelligence

Individuals high in innovativeness are more likely to experiment with and embrace novel technologies, which, in turn, can lead to greater opportunities for personal growth and achievement (Parasuraman & Colby, 2015). Research has shown that individuals with high levels of innovativeness tend to be more goal-oriented, seeking achievement through the use of advanced tools that offer efficiency, effectiveness, and personalized solutions (Loogma et al., 2012). Furthermore, the adoption of innovative technologies like GenAI is often driven by the expectation that these tools will not only satisfy utilitarian needs but also foster a sense of accomplishment through their use (Butler et al., 2008). Hence, it can be hypothesized that:

H14. Innovativeness will positively impact achievement

Innovativeness is a stable personality trait that plays a crucial role in shaping how individuals perceive and interact with new technologies, particularly in terms of perceived enjoyment. According to Agarwal and Prasad (1998), innovativeness remains stable and unchanged regardless of the type of information technology, meaning that individuals with higher levels of innovativeness are more likely to develop positive attitudes toward new technologies, including GenAI. Numerous studies have demonstrated a positive relationship between innovativeness and hedonic motivation, which is closely associated with perceived enjoyment. For instance, Kim et al. (2015) found that innovative perceptions significantly boost hedonic motivation, or the enjoyment derived from an activity. This is especially noticeable in college students' willingness to engage with new products,

such as sports products, driven by their innovative mindset. Similarly, Lee and Lee (2021) discovered that personal innovativeness positively influences hedonic motivation when using intelligent voice assistant systems, indicating that individuals with higher innovativeness experience greater enjoyment from using advanced technologies. In the context of wearable technology, studies have shown that the degree of consumers' innovativeness is positively related to their hedonic motivation, which, in turn, influences their intention to continue using the technology. For example, Hong et al. (2017) found that innovativeness influences hedonic motivation and affects users' intentions to continue using smartwatches. This aligns with the findings of Ha et al. (2025), who also found that higher levels of innovativeness led to greater perceived enjoyment and continued use of technology. As early adopters of GenAI, students with high innovativeness are likely to experience more positive emotional responses when using this technology. These individuals are adept at utilizing GenAI to enhance their learning experiences, further increasing their perceived enjoyment (Wang et al., 2023). Therefore, it can be hypothesized that

H15. Innovativeness will positively impact perceived enjoyment

Research suggests that individuals who score high in innovativeness tend to be more proactive in engaging with new products and technologies, which in turn impacts how they perceive and experience social presence in digital environments (Rogers, 2003). Moreover, the researcher also suggested that as early adopters, innovative individuals often shape the social dynamics of new technologies by forming opinions and influencing others, further enhancing the social presence they experience in these environments. Innovators are typically early adopters of technology, and their willingness to explore new technologies allows them to feel more connected and engaged with these platforms, enhancing their sense of social presence (Moore & Benbasat, 1991). Innovativeness drives individuals to seek out social connections and opportunities for interaction within digital environments. As such, highly innovative individuals are likely to perceive a higher level of social presence when using new technologies, such as GenAI. Their proactive engagement with these tools enables them to experience a more meaningful and connected interaction with the technology, which strengthens their sense of social presence (Venkatesh et al., 2003). Thus, it can be hypothesized that

H16. Innovativeness will positively impact social presence

Individuals with a high level of innovativeness tend to be early adopters of new products, and these early buyers are often seen as opinion leaders in their respective product categories (Rogers, 2003). According the researcher, early adopters, due to their involvement and knowledge, are not only among the first to experience the latest products but are also sought after for their opinions on new commodities. Their ability to adopt and use new technology before others contributes to their perceived status within their social circles. This tendency to adopt new products is closely linked with a desire to be seen as socially advanced or ahead of the curve, which is often associated with increased social status (Özkeş & Kaya, 2015). They also affirmed that this relationship between innovativeness and status is particularly evident in the technology adoption process. As individuals with high innovativeness are seen as more knowledgeable and capable in using new technologies, they are often regarded with higher social esteem. The desire for status is a powerful motivator for innovative individuals, as they seek to maintain or elevate their position in their social group by being the first to adopt and use new products or technologies. In the context of GenAI, innovative students, who are early adopters, may perceive their engagement with this technology as a way to

enhance their social status, further reinforcing their intention to use it for educational purposes. Therefore, it can be hypothesized that

H17. Innovativeness will positively impact status

The relationship between curiosity and innovativeness is a matter of scholarly debate. Their observed correlation may represent a spurious relationship that stems from a common basis in the personality trait "Openness to Experience" (Abdullah, Omar, & Panatik, 2016; Litman & Jimerson, 2004). The two constructs are fundamentally different in their goals and scope. Personality curiosity is primarily an intrinsic cognitive motivation focused on resolving information gaps (Loewenstein, 1994; Litman & Spielberger, 2003), whereas innovativeness is an extrinsic action-oriented process that requires the adoption, promotion, and implementation of novel ideas that are inherently risky (Scott & Bruce, 1994). Since the proactive application and risk-taking required for innovativeness are not included in the core definition of curiosity, trait curiosity should be considered a separate construct rather than a direct antecedent of innovativeness. Therefore, the relationship between curiosity and innovativeness was not investigated in this study.

Based on the aforementioned arguments along with testing the moderating potiential of demographic variables, we suggest the research framework and hypotheses in Figure 2 that includes:
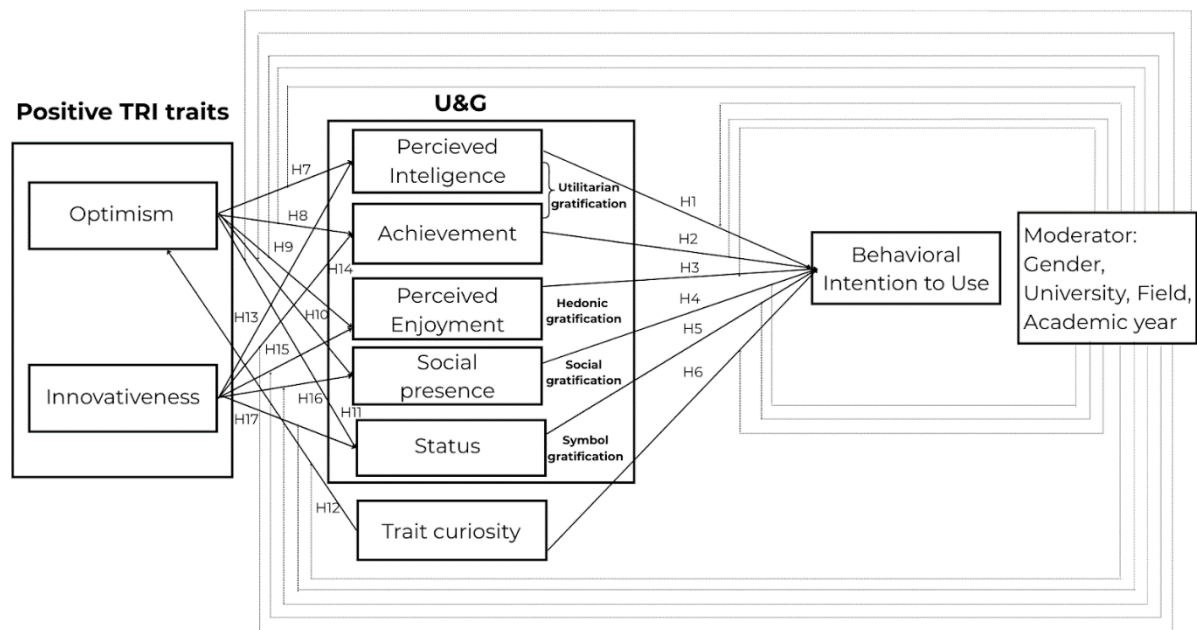

Fig. 2. Proposed Research Model

4. Methodology and Data

4.1. Measurement instruments

To test the theoretical constructs in this study, a questionnaire-based survey was developed. Constructs and measurement items were adapted with minor modifications from the literature to create the questionnaire. The measurement items are sourced from the works of (Bartneck et al., 2009), Taylor and Todd (1995), Davis et al. (1992), Stafford et al. (2004), Moore and Benbasat (1991), Parasuraman (2000), Kashdan et al. (2009), and (Venkatesh et al., 2012). All primary measurement

items were assessed using five-point Likert scales, where responses ranged from "strongly disagree" (1) to "strongly agree" (5).

In addition to the main constructs, the questionnaire included four demographic variables: gender, university location, field of study, and academic year. The initial questionnaire was developed in English and underwent a content validity review by experts from a university. To accommodate the Vietnamese context of data collection, the English version was translated into Vietnamese by a professional translator.

The survey was administered online using Google Forms and distributed through email and social networks. A total of 594 Vietnamese university students were contacted, resulting in 339 valid responses. Of the 339 valid responses, the gender ratio was almost balanced (50.6% female, 49.4% male). The majority of participants came from universities in the Central region (61.2%), followed by the South (23.7%) and the North (15.1%). In terms of academic discipline, students from the economics and business-related majors accounted for the majority (48.5%), social sciences and humanities (21.6%) and other sectors (29.9%). In terms of academic year, while Senior students (third year and above) accounted for a larger proportion at 66% and Fresher students (first and second year) accounted for 34%.

After data collection, coding and processing techniques were employed to achieve the research objectives, primarily utilizing SPSS 27.0 and Smart PLS 4.0. Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied to test the research model and hypotheses.

5. Results and Discussions

5.1. Measurement model

In order to verify measurement model, all observed variables of 9 latent variables were used to conduct the partial least squares structural equation modeling (PLS-SEM). The analysis results show that the outer loadings for each of the latent variable of the present study were sufficiently greater than 0.5. The composite reliability (CR) coefficients for each of the latent variable ranged from 0.751 to 0.858, which indicating strong reliability of the measures. The average variance extracted (AVE) have sufficiently greater than 0.5, thus the study demonstrated adequate convergent validity (see Table 1). The shared variance between factors was below the square root of the AVE of the individual factors as shown in Table 2, ratifying the discriminant validity. The results of cross loading show that all individual items are loaded higher on their respective constructs than on the other constructs. The square root of AVE was higher than the correlations among the latent variables. Therefore, the discriminant validity of the measurement model in this study is acceptable. VIF of all observed variables are less than 3; thus, multicollinearity is not a concern in this study. The details are presented in Table 1 and Table 2.

Table 1. Convergent Validity

Factor	Cronbach's Alpha (α)	Composite Reliability (CR)	Variance Inflation Factor (VIF)	Average Variance Extracted (AVE)
Optimism (OPT)	0.857	0.858	1.809	0.586
Innovativeness (INN)	0.806	0.807	1.809	0.563

Perceived Intelligence (PIN)	0.815	0.840	1.720	0.582
Achievement (ACH)	0.853	0.853	1.801	0.773
Perceived Enjoyment (PEN)	0.724	0.751	1.552	0.641
Social Presence (SLP)	0.781	0.786	1.695	0.607
Status (STA)	0.831	0.832	2.600	0.598
Trait Curiosity (TCU)	0.831	0.831	1.785	0.748
Behavioral Intention to Use (BIU)	0.798	0.803		0.623

Table 2. Discriminant Validity

	ACH	BIU	INN	OPT	PEN	PIN	SLP	STA	TCU
ACH	**0.879**[a]	0.602[c]	0.372[c]	0.683[c]	0.231[c]	0.306[c]	0.388[c]	0.757[c]	0.630[c]
BIU	0.469[b]	**0.789**[a]	0.725[c]	0.849[c]	0.358[c]	0.495[c]	0.561[c]	0.703[c]	0.727[c]
INN	0.329[b]	0.596[b]	**0.751**[a]	0.779[c]	0.43[c]	0.578[c]	0.566[c]	0.604[c]	0.656[c]
OPT	0.586[b]	0.706[b]	0.699[b]	**0.765**[a]	0.532[c]	0.596[c]	0.671[c]	0.812[c]	0.834[c]
PEN	0.183[b]	0.278[b]	0.342[b]	0.432[b]	**0.800**[a]	0.700[c]	0.644[c]	0.516[c]	0.391[c]
PIN	0.258[b]	0.402[b]	0.480[b]	0.511[b]	0.538[b]	**0.763**[a]	0.648[c]	0.587[c]	0.463[c]
SLP	0.319[b]	0.447[b]	0.458[b]	0.551[b]	0.482[b]	0.516[b]	**0.779**[a]	0.660[c]	0.524[c]
STA	0.637[b]	0.573[b]	0.509[b]	0.693[b]	0.401[b]	0.494[b]	0.534[b]	**0.773**[a]	0.752[c]
TCU	0.530[b]	0.597[b]	0.565[b]	0.706[b]	0.306[b]	0.384[b]	0.424[b]	0.628[b]	**0.865**[a]

[a] *Square root of the average variance extracted (AVE) of each latent variable*

[b] *Correlation between latent variables*

[c] *HTMT value*

5.2. Hypotheses testing

Multiple PLS-SEM analyses were used to examine the interrelationships between the factors of Perceived Intelligence, Achievement, Perceived Enjoyment, Social Presence, Status, Trait Curiosity and Behavioral Intention to Use towards GenAI as well as the interrelationships between Optimism, Innovativeness and Perceived Intelligence, Achievement, Perceived Enjoyment, Social Presence, Status, Trait Curiosity. The results in Table 3 show the evaluation of the significance and relevance of the path factors in the structural model using bootstrapping with 5000 samples. The path coefficients show that thirteen over seventeen structural relationships are statistically significant. PLS-SEM results for all bootstrap models provide confirmation for the hypotheses as shown in Table 3.

Table 3. Hypotheses testing results based on testing structural equation models

Hypotheses	β	Std.	t-value	p-value	VIF	Results
H1. Perceived Intelligence (PIN) → BIU	0.108	0.055	1.992	0.046	1.720	Accepted
H2. Achievement (ACH) → BIU	0.159	0.067	2.410	0.016	1.801	Accepted

H3. Perceived Enjoyment (PEN) → BIU	-0.037	0.057	0.654	0.513	1.552	Rejected
H4. Social Presence (SLP) → BIU	0.136	0.057	2.400	0.016	1.695	Accepted
H5. Status (STA) → BIU	0.156	0.076	2.106	0.035	2.600	Accepted
H6. Trait Curiosity (TCU) → BIU	0.326	0.063	5.254	*< 0.001*	1.785	Accepted
H7. OPT → Perceived Intelligence (PIN)	0.344	0.061	5.702	*< 0.001*	1.809	Accepted
H8. OPT → Achievement (ACH)	0.662	0.057	11.689	*< 0.001*	1.809	Accepted
H9. OPT → Perceived Enjoyment (PEN)	0.367	0.068	5.438	*< 0.001*	1.809	Accepted
H10. OPT → Social Presence (SLP)	0.442	0.061	7.417	*< 0.001*	1.809	Accepted
H11. OPT → Status (STA)	0.637	0.048	13.452	*< 0.001*	1.809	Accepted
H12. Trait Curiosity (TCU) → OPT	0.706	0.037	19.269	*< 0.001*	1.000	Accepted
H13. INN → Perceived Intelligence (PIN)	0.250	0.070	3.553	*< 0.001*	1.809	Accepted
H14. INN → Achievement (ACH)	-0.113	0.064	1.821	0.069	1.809	Rejected
H15. INN → Perceived Enjoyment (PEN)	0.097	0.075	1.307	0.191	1.809	Rejected
H16. INN → Social Presence (SLP)	0.163	0.070	2.341	0.019	1.809	Accepted
H17. INN → Status (STA)	0.084	0.057	1.510	0.131	1.809	Rejected

5.3. Analysis of the Moderating Effect

The results of the Partial Least Squares Multi-Group Analysis (PLS-MGA) conducted to examine the moderating effect of gender show that there were no statistically significant differences between the structural paths of the two gender groups (male vs. female), as the p-values for all path comparisons were above the 0.05 threshold. These findings suggest that gender does not have a moderating effect on the relationships outlined in the model.

For the morderating effect of geographic region (divided into three groups: Northern, Central, and Southern Vietnam) on the hypothesized relationships within the research model, PLS-MGA resutls confirmed morderating effect of geographic region on the relationship between Trait Curiosity and Behavioral Intention to Use (H6), between Innovativeness and Perceived Enjoyment (H15), and between Innovativeness and Social Presence (H16); as shown in Table 4.

Table 4. The accepted results of the PLS-Multi-Group Analysis (PLS-MGA),
conducted to examine the moderating effect of regional universities

Hypothesis	β (Northern-Central)	β (Northern-Southern)	β (Central-Southern)	p-Value new (Northern-Central)	p-Value new (Northern-Southern)	p-Value new (Central-Southern)
H6. TCU → BIU	-0.123	0.235	0.358	0.508	0.276	0.024
H15. INN → PEN	0.139	-0.378	-0.518	0.527	0.106	0.001
H16. INN → SLP	-0.13	-0.367	-0.237	0.499	0.049	0.071

For the morderating effect of academic discipline (categorized into three academic groups: Business and Economics, Social Sciences and Humanities, and Other Disciplines) on the hypothesized relationships within the research model, PLS-MGA resutls confirmed morderating effect of learning experience level on the relationship between Optimism and Perceived Intelligence (H7), between Optimism and Status (H11), and between Innovativeness and Perceived Intelligence (H13); as shown in Table 5.

Table 5. The accepted results of the PLS-Multi-Group Analysis (PLS-MGA),
conducted to examine the moderating effect of academic discipline

Hypothesis	β (B&E - SSH)	β (B&E - Other)	β (SSH - Other)	p-Value new (B&E - Other)	p-Value new (B&E - Other)	p-Value new (SSH - Other)
H7. OPT → PIN	-0.329	-0.022	0.308	0.034	0.885	0.045
H11. OPT → STA	-0.245	-0.120	0.125	0.047	0.272	0.319
H13. INN → PIN	0.278	-0.227	-0.504	0.136	0.150	0.005

For the morderating effect of learning experience level based on academic year (categorized into two categories: fresher vs. senior) on the hypothesized relationships within the research model, PLS-MGA resutls confirmed morderating effect of learning experience level on the relationship between Achievement and Behavioral Intention to Use (H2); as shown in Table 6.

Table 6. The accepted results of the PLS-Multi-Group Analysis (PLS-MGA),
conducted to examine the moderating effect of learning experience level

Hypothesis	β (Fresher-Senior)	p-Value new (Fresher - Senior)
H2. ACH → BIU	-0.271	0.034

5.4. Analysis of the Mediating Effect

To assess the mediating effect of a variable in the relationship between two other variables, the bootstrapping method proposed by Zhao et al. (2010) was employed. Table 7 confirmed mediation effects of proposed research model by statistically significant bootstrapped indirect effects that have t-value greater than 1.96 at the 5% significance level (Zhao et al., 2010).

Table 7. Results of Mediation Analysis based on bootstrapping method

Mediating Effect	t-value	p-value	Results
OPT → PIN → BIU	1.843	0.065	Rejected
OPT → ACH → BIU	2.34	0.019	Accepted
OPT → PEN → BIU	0.626	0.531	Rejected
OPT → SLP → BIU	2.202	0.028	Accepted
OPT → STA → BIU	2.064	0.039	Accepted
TCU → OPT → PIN	5.454	< 0.001	Accepted
TCU → OPT → ACH	9.466	< 0.001	Accepted
TCU → OPT → PEN	5.122	< 0.001	Accepted

TCU → OPT → SLP	6.549	< 0.001	Accepted
TCU → OPT → STA	10.078	< 0.001	Accepted
TCU → OPT → PIN→ BIU	1.845	0.065	Rejected
TCU → OPT → ACH → BIU	2.375	0.018	Accepted
TCU → OPT→ PEN →BIU	0.624	0.532	Rejected
TCU → OPT → SLP → BIU	2.183	0.029	Accepted
TCU → OPT → STA → BIU	2.04	0.041	Accepted
INN → PIN → BIU	1.595	0.111	Rejected
INN → ACH → BIU	1.475	0.14	Rejected
INN → PEN -→ BIU	0.473	0.636	Rejected
INN → SLP → BIU	1.501	0.133	Rejected
INN → STA → BIU	1.024	0.306	Rejected

5.5. Discussion

The results of testing the relationships between Perceived Intelligence, Achievement, Social Presence, Status, Trait Curiosity and Behavioral Intention to Use towards GenAI show that these relationships are statistically significant. These confirmations are aligns with previous studies such as (Moussawi et al., 2023; Dong et al., 2017), (Deci & Ryan, 2000), Rains et al., 2016; Shin & Biocca, 2018   Kim & Park, 2013; Venkatesh & Davis, 2000, Jirout & Klahr, 2012; Kashdan et al., 2009 . However, in the Vietnamese higher education context, Perceived Enjoyment had not been proved its effect on students' intention to adopt GenAI for learning. This could be explained the functional-oriented mindset of students when using GenAI tools for learning. In academic settings where performance outcomes, efficiency, and task completion are prioritized, students may not place high value on hedonic experiences. For many, the use of GenAI is perceived as a means to an end, rather than a source of intrinsic pleasure. As a result, perceived enjoyment may not translate into behavioral intention unless it is coupled with clear cognitive or performance benefits.

The research results also confirm the effect of Optimism on Perceived Intelligence, Achievement, Perceived Enjoyment, Social Presence and Status as well as the effect Trait Curiosity on Optimism. Besides, the effect of Innovativeness on Perceived Intelligence and Social Presence were also confirmed, but the emperical results have not confirmed the effect of Innovativeness on Achievement, Perceived Enjoyment and Status.

For the relationship between Innovativeness and Achievement, a possible explanation for this divergence may lie in the nature of the technology and the maturity level of its adoption. As GenAI is still relatively new in educational settings in Vietnam, many students, regardless of their level of innovativeness, may still be in an exploratory phase. In such cases, even highly innovative students may not yet have discovered or consistently applied the tool's capabilities in a way that results in tangible academic achievement. Instead, they may be using GenAI sporadically or for peripheral tasks, limiting its perceived contribution to learning outcomes.

For the relationship between Innovativeness and Perceived Enjoyment, in Vietnamese context, This unexpected result may be attributed to several factors. First, students' exposure to GenAI might

still be in an exploratory phase, meaning that even innovative individuals have not fully developed personalized or engaging use patterns that translate into emotional gratification. Unlike entertainment-oriented applications, GenAI tools may require structured goals to elicit enjoyment, which spontaneous experimentation alone may not fulfill. Second, the educational context in which GenAI is used might limit the manifestation of hedonic responses. Many students may approach the tool from a task-driven mindset (e.g., for homework, translation, or summarization), reducing the likelihood that experimentation leads to genuine enjoyment. This contrasts with prior findings (e.g., Yi et al., 2006; Jin, 2022) where perceived enjoyment was found to be a key outcome of innovativeness, often in settings that prioritize play, discovery, or entertainment. Additionally, previous studies (e.g., Aldahdouh et al., 2020) have cautioned that highly innovative users may engage with technology in fragmented or overly exploratory ways, which may generate curiosity but not necessarily sustained pleasure. In such cases, novelty becomes a goal in itself, leading to a cycle of shallow engagement rather than deep, rewarding use.

For the relationship between Innovativeness and Status, several potential explanations may account for this finding. First, while innovativeness reflects a tendency to explore and adopt novel technologies, this trait may be internally motivated and not necessarily associated with a desire for social recognition. In contrast to Optimism, which may involve broader beliefs in technology's societal value, Innovativeness may focus more on personal curiosity and experimentation, which may not be visible or valued socially. Second, the normative context of university environments could play a role. In many academic settings, the use of AI tools like GenAI may not yet be widely recognized as a status symbol. Early adopters might even be met with skepticism or indifference, especially if peers or instructors view AI usage as unconventional or academically questionable. As such, the symbolic benefits of innovativeness may be muted or context-dependent.

6. Conclusion

GenAI is reshaping multiple industries include education across the globe; however, empirical studies investigating the psychological and behavioral drivers behind students' use of GenAI in learning contexts are scarce. The results of this study complement the lack of empirical research on factors affecting behavioral intention to adopt GenAI for learning purpose in the world and especially in Vietnamese higher education context. The study also contributed to an increase in the literature examining the role of positive technology readiness traits, trait curiosity as well as other factors in the U&G model on behavioral intention to use GenAI.

Beside of our study's main contribution that adds into the existing body of knowledge, we also recognize its limitations, mostly regarding the sampling with typically young, highly educated people as responders. The respondents' behavioral patterns might diverge to some extent in comparison with the population average. With the behaviors that are mostly more pioneering and rapider to adopt new technologies, this sampling may have biased the effects. In addition, the study has not yet examined the role of control variables such as technology proficiency, language proficiency, or the specific type of GenAI tool respondents use, which may significantly influence their perceptions and intentions. Future research can be constructed based on this study by adding the above control variables as well as examining the proposed model in different age groups or applying this model to other countries and also other contexts. Moreover, future research should

make a longitudinal study to yield better results than a cross-sectional one because the relationship among factors that affecting on behavioral intention to use in different phases of adoption would provide more meaningful insights. Finally, to enrich scale development and interpretive discussion, future studies could further analyze the specific context of Vietnam, including educational culture, AI policies, and the current state of academic infrastructure.

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